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Applied use of growing degree days to refine optimum times for nitrogen stress sensing in winter wheat

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Abstract

Variable influence of the environment on early-season plant growth leads to similarly variable yield levels from year to year. This study was conducted to determine the ideal point in the growing season when normalized difference vegetation index (NDVI) sensor readings were highly correlated with grain yield. For each site-year, NDVI readings were collected at least seven times from December through April. Readings were collected from two long-term experiments where an N response was expected in plots that historically received different N rates. The number of days from planting to sensing where growing degree days (GDD) were more than 0 (GDD > 0) was tabulated by site-year for all dates when NDVI data were collected. The r^2 was computed for NDVI versus final grain yield at all sensing dates and plotted against the respective GDD > 0 when readings were taken. Linear plateau models were used to determine the point when the r^2 peaked. Averaged over 3 yr (2016–2018), the optimum GDD > 0 needed to predict grain yield using NDVI in both long-term trials was between 97 and 112. Use of the GDD > 0 as a numeric metric to delineate the best time and date to collect NDVI readings and predict yield potential can then be used to formulate accurate midseason fertilizer N rates. Adhering to quantitative GDD > 0 data is much more reliable than using subjective morphological scales. These critical GDD values can be reported on a day-to-day, by-location basis (mesonet.org) for in-season producer use.

1 | INTRODUCTION

Understanding how the weather might affect grain yield in a timely manner to make mid-season decisions based on that specific growing environment is lacking. With the advent of day-to-day county and within-county weather information, including rainfall, temperature, and composite growth statistics, encumbering this information within mid-season algorithms for water, fertilizer, and pesticide application is now possible (Girma, Mack, Taylor, Solie, & Raun, 2007; Lorite, Ramírez-Cuesta, Cruz-Blanco, & Santos, 2015).

Work by Bannayan, Crout, and Hoogenboom (2003) with the CERES model showed that using stochastically generated weather data could substitute for measured data. This then provides a reliable forecast for wheat (*Triticum aestivum* L.) grain yield, which starts in June and continues until the end of the season for conditions in the United Kingdom.

In crop nutrient management, a commonly used vegetative index is the normalized difference vegetation index (NDVI) (Piedallu et al., 2019). Where NDVI is calculated based on reflectance of red and near-infrared spectral bands (Tucker,

Abbreviations: GDD, growing degree days; NDVI, normalized difference vegetation index; RI, response index.

TABLE 1 Experimental data included in the analysis, year established, annual average rainfall, and range in annual rainfall

Experiment	Longitude, latitude	Year started	Annual average Rainfall (1994–2018) mm	Range (1994–2018)	2016	2017	2018	Mean annual temperature °C
222	36° 7′ 7″, N 97° 5′ 30″ W	1969	922	606–1493	784	1095	937	15.0
502	36° 23′ 13″ N, 98° 6′ 29″ W	1970	771	503–1314	716	849	854	15.6

Townshend, & Goff, 1985). Furthermore, NDVI obtained using optical sensors is used to estimate chlorophyll content, crop N content, biomass, and yield (Hatfield, Gitelson, Schepers, & Walthall, 2008; Solie, Raun, Whitney, Stone, & Ringer, 1996; Stone et al., 1996).

Studies conducted by Raun et al. (2001) recognized that mid-season wheat grain yield potential could be predicted by including growing degree days (GDD) combined with NDVI readings. Related work by Russelle, Wilhelm, Olson, and Power (1984) showed that using GDD, rather than days, as the divisor led to the recognition of physiological differences, previously masked by normal crop response to temperature.

For this study, the number of days was determined from planting to sensing, where GDD was computed as (Tmin + Tmax)/2 – 4.4°C. The 4.4°C threshold is commonly used for winter wheat Oklahoma Mesonet (2018) and is a metric that conveys a benchmark for growth. This followed work demonstrating that NDVI readings alone were useful for predicting dry and/or wet plant biomass (Stone et al., 1996).

Similar work by Freeman, Girma, Mullen, Teal, and Raun (2007) showed that NDVI sensor readings, combined with mid-season estimates of plant height in maize, could be used to predict grain yields. Both the wheat and maize research targeted growth rate by encumbering either days from planting to sensing and/or plant height measurements.

Related work by Dhital and Raun (2016) reported a wide range in optimum maize N rates for 213 site-years of data, suggesting the need to adjust N rates by year and location. Adjusting N rates by year and location would be facilitated by having refined, time-sensitive indices for mid-season yield prediction and by tailoring those readings to the times when N use efficiency was optimized. This work was considered to be prudent considering that N use efficiency has been problematic, averaging 33% for many cereal crop production systems and environments (Raun & Johnson, 1999).

Stone et al. (1996) used two NDVI readings and GDD accumulated between the two readings to refine yield estimates. Nonetheless, they did not recognize the value of GDD accumulated from planting date to sensing date. Over time, this group realized the importance of climatological inputs in addition to NDVI, which could then be combined with other years and locations, thus facilitating regional equation development for predicting yield (Lukina et al., 2001). Yield potential (YP_0) estimates were calculated by dividing the NDVI reading by the number of days from planting to sensing when GDD > 0. Lukina et al. (2001) and Raun et al. (2001) later advanced this in-season estimate of yield. The objective of this work was to look further into the use of GDD and to identify ranges in cumulative GDD that could more accurately delineate those periods when winter wheat grain yield could be predicted.

TABLE 2 Soil test parameters and test levels present in selected treatments for Experiment 222 and Experiment 502 from samples collected prior to planting in 2016

Experiment	Treatment	P	K	pH	Organic C	Total N
		mg kg^{-1}			g kg^{-1}	
222	0–0–0	8.44	45.21	5.52	8.37	0.97
	0–60–40	8.48	21.71	5.42	8.63	1.00
	80–60–40	12.59	48.22	5.19	8.91	1.05
502	0–0–0	8.48	21.71	6.24	8.33	0.93
	0–40–60	5.81	34.79	6.24	8.53	0.89
	80–40–60	10.88	39.47	5.59	8.45	0.94

2 | MATERIALS AND METHODS

Two long-term trials were selected for comprehensive NDVI sensor readings over the active winter wheat growing cycle in 2016, 2017, and 2018. Site and climate information for Experiment 222 and Experiment 502 are outlined in Table 1. Additional soil test data are reported for specific treatments in Table 2. Both trials used a randomized complete block experimental design with four replications. Soil samples (0–15 cm, 15 cores per plot) were collected prior to planting. A soil subsample was taken from each treatment, dried at 75°C, and ground to pass a 240-mesh screen, and total N was determined using a LECO Truspec CN dry combustion analyzer (Schepers, Francis, & Thompson, 1989). The Mehlich III extractant (Bond, Maguire, & Havlin, 2006) was used to determine soil test values for P and K. These values and added site data are reported in Tables 2, 3 and 4; these tables also report the treatment structure for Experiments 222 and 502.

TABLE 3 Treatment structure for Experiment 222, Stillwater, OK

Treatment	Preplant N rate[a] kg N ha^{-1}	Preplant P rate[b] kg P ha^{-1}	Preplant K rate[c] kg K ha^{-1}
1[d]	0	30	37
2[d]	45	30	37
3[d]	90	30	37
4[d]	135[e]	30	37
5	90	0	37
6	90	15	37
7	90	45	37
8	90	30	0
9	90	30	74
10[d]	0	0	0
11	135[e]	45	74
12	135[e]	45	0
13	90	30	37 (Sul-Po-Mag)

[a]Nitrogen applied as 46–0–0 (urea).
[b]Phosphorus applied as 0–46–0 (triple super phosphate).
[c]Potassium applied as 0–0–60 (potash).
[d]Yield potential plot.
[e]Split 135 kg N rates to 67.5 kg N (fall) and 67.5 kg N (spring).

TABLE 4 Treatment structure for Experiment 502, Lahoma, OK

Treatment	Preplant N rate[a] kg N ha^{-1}	Preplant P rate[b] kg P ha^{-1}	Preplant K rate[c] kg K ha^{-1}
1[d]	0	0	0
2[d]	0	20	56
3[d]	22.5	20	56
4[d]	45	20	56
5[d]	67.5	20	56
6[d]	90	20	56
7[d]	112.5	20	56
8	67.5	0	56
9	67.5	10	56
10	67.5	30	56
11	67.5	40	56
12	67.5	30	0
13	112.5	40	56
14	67.5	20	56 (Sul-Po-Mag)

[a]Nitrogen applied as 46–0–0 (urea).
[b]Phosphorus applied as 0–46–0 (triple super phosphate).
[c]Potassium applied as 0–0–60 (potash).
[d]Yield potential plot.

Over the course of the 2016 winter wheat growing season, 10 and 11 NDVI sensor readings were collected for Experiment 222 and Experiment 502, respectively. For the 2017 growing season, seven readings were collected at both sites. In 2018, 18 and 23 readings were taken from Experiments 222 and 502, respectively.

For both sites and all years, readings began at or near the Feekes 2 physiological growth stage (Large, 1954) and ended at or near Feekes 11. Dates for preplant fertilizer applications, planting, top-dress applications, and grain harvest for Experiment 222 and Experiment 502 for the years 2016, 2017, and 2018 cropping seasons are reported in Table 5. Sensor NDVI data were collected over a wide range of GDD > 0 for both sites and all for 3 yr. For Experiment 222, these ranges were 64–137 (2016), 90–149 (2017), and 17–126 (2018). For Experiment 502, ranges in GDD > 0 when sensor readings were taken were 48–127 (2016), 78–143 (2017), and 43–135 (2018).

Grain yield was recorded, and analysis for total grain N was completed for each plot at both sites. For each sensing event and location, GDD > 1 were retrieved from the Mesonet Wheat Growth Day Counter (Mesonet, 2018). The GreenSeeker NDVI active sensor (Trimble) was used to collect sensor data at a rate of 70 readings m^{-2} when walking at a speed of 5 km h^{-1} and held 70 cm above the wheat canopy. Since the beginning of the use of the GreenSeeker for yield prediction, more than four readings per season and/or site had not been accomplished. This analysis encumbered a much higher frequency of readings over the season. It was thus assumed that a larger and more robust NDVI dataset could deliver more accurate information for modeling growth and resultant grain yields.

The r^2 for each NDVI/yield relationship was plotted as a function of corresponding GDD > 0. A linear-plateau model was then fit to this relationship to determine if a viable joint and/or intersection existed (SAS Institute, 2011). This would be apparent if an increase in GDD > 0 no longer resulted in the improvement of the r^2 value (Nelson, Voss, & Pesek, 1985). Furthermore, it was anticipated that a "plateau" could be established and where improved correlation was no longer attainable or where the r^2 values (NDVI versus yield) no longer increased. This intersection (linear transition to a plateau, using GDD > 0) would, in theory, be the ideal point in a given season when predicting wheat grain yield using NDVI was maximized (i.e., the point where the correlation between NDVI and wheat grain yield was maximized). This applied linear-plateau model programmed in SAS (2011) was first defined and advanced at North Carolina State University (Anderson & Nelson, 1975; Cate & Nelson, 1971).

The current algorithm for dryland winter wheat, obtained from Oklahoma State University (2018), was used to predict yield potential (YP_0).

$$YP_0 = 1711^{*}e^{(INSEY^{*}137.2)} \quad (1)$$

where in-season estimate of yield (INSEY) is calculated by dividing sequential NDVI by the number of cumulative GDD. This algorithm was developed using the methodology described by Raun et al. (2005). Furthermore, the relationship

TABLE 5 Dates for preplant applications, planting, top-dress applications, and grain harvest for Experiment 222 and Experiment 502; 2016, 2017, and 2018 cropping seasons

	Experiment 222			Experiment 502		
	2016	2017	2018	2016	2017	2018
Preplant	24 Sept. 2015	29 Sept. 2016	21 Sept. 2017	24 Sept. 2015	13 Oct. 2016	22 Sept. 2017
Plant	12 Oct. 2015	21 Oct. 2016	20 Oct. 2017	20 Oct. 2015	18 Oct. 2016	13 Oct. 2017
Top-dress	1 Mar. 2016	24 Feb. 2017	12 Mar. 2018	NA[a]	NA	NA
Harvest	9 June 2016	1 June 2017	14 June 2018	11 June 2016	13 June 2017	6 June 2018

[a]Not available.

TABLE 6 Linear-plateau models that delineate the optimum growing degree days (GDD) > 0 for predicting wheat grain yield using in-season normalized difference vegetative index sensor data

Experiment[a]	Season	Equation	r^2
222	2016, 2017	$y = 0.0183x - 1.2148, x < 112 y = 0.822, x > 112$	0.93
502	2016, 2017	$y = 0.0192x - 0.947, x < 97 y = 0.9196, x > 97$	0.96

Note. Joints listed for days where growing degree days > 0 are in theory the ideal climatologically identifiable point in a given season, where predicting wheat grain yield using normalized difference vegetative index was maximized.
[a]Experiment 222 and Experiment 502 including the cropping seasons for 2016 and 2017.

between predicted and actual grain yield using sequential NDVI readings over the entire growing season was explored for each site-year. In addition, the response index (RI) for each treatment at each respective GDD was adjusted using the following equation (http://www.nue.okstate.edu/Yield_Potential.htm):

$$\mathrm{RI} = 1.69^{*}\,(\mathrm{RI} - \mathrm{NDVI}) - 0.70 \quad (2)$$

Equation (2) is currently used for making on-line N recommendations.

The value for RI-NDVI was calculated by dividing the NDVI of the treatment receiving the highest N rate by the NDVI in the zero-N check plot for each trial and year. The RI predicts the crop response to additional applied N. This value varies spatially and temporally and is further described by Johnson and Raun (2003) and Raun et al. (2005). This RI was plotted over the entire season for each site-year

Moreover, YP_0 and RI were used to calculate yield with added fertilizer N (YP_N) using the following equation:

$$\mathrm{YP}_\mathrm{N} = \mathrm{YP}_0{}^{*}\mathrm{RI} \quad (3)$$

These were further used to calculate N required using the following equation:

$$R = 23.9^{*}\,\frac{\mathrm{YP}_\mathrm{N} - \mathrm{YP}_0}{\eta} \quad (4)$$

where R is the N application rate (kg ha^{-1}), 23.9 is the percentage of N by weight present in wheat grain multiplied by a conversion factor, and η is a fertilizer use efficiency factor ($0.5 \leq \eta \leq 0.7$). The calculated N rate was also plotted over the entire season for each site-year.

A detailed description of all these variables, equations, calculation, and methodology are noted in Raun et al. (2001, 2002, 2005).

3 | RESULTS AND DISCUSSION

The linear-plateau relationship between recorded GDD > 0 for each data collection time where the r^2 for the NDVI and yield were determined is reported in Table 6 for all site-years. The joint or beginning of the plateau was the point where an increase in the total number of days where GDD > 0 no longer resulted in improved correlation or a higher r^2 value. In theory, collecting NDVI data at or near to this point would be ideal.

For the 2016 and 2017 data included, this work showed that having approximately 97 and 112 days when GDD > 0 was ideal (Experiment 502 and Experiment 222) in terms of a defined in-season–specific point in time when NDVI readings should be collected (Figures 1 and 2; Table 6). The corresponding Feekes growth stages for this GDD range was Feekes 4 and Feekes 5, which are appropriate for top-dress N application. A robust amount of data was collected in 2018 at both sites, but this information was not used. At both sites, stand establishment was poor, and although winter wheat can often compensate for poor stands, this did not occur at either 2018 site, resulting in nonusable data.

This in-season–specific point in time (GDD > 0 between 97 and 112) would also be the best time to make in-season N fertilizer rate recommendations. Even though including different locations (Stillwater and Lahoma) and multiple years (2015–2016, 2016–2017, 2017–2018) where seasonal temperature and cumulative rainfall varied, the optimum GDD > 0 needed

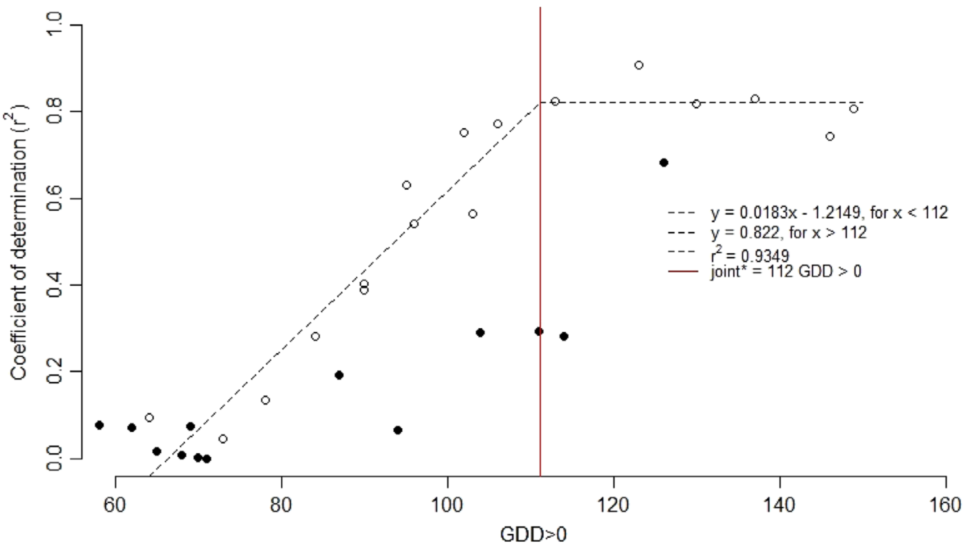

FIGURE 1 Correlation of normalized difference vegetation index versus winter wheat grain yield, for readings collected over the season where the number of days from planting to sensing (growing degree days more than 0 [GDD > 0]) ranged from 64 to 149. Growing degree days was calculated as (Tmin + Tmax)/2 – 4.4°C. Data are for Experiment 222, Stillwater, OK, 2016 and 2017. Data not used for 2018 are represented by black dots

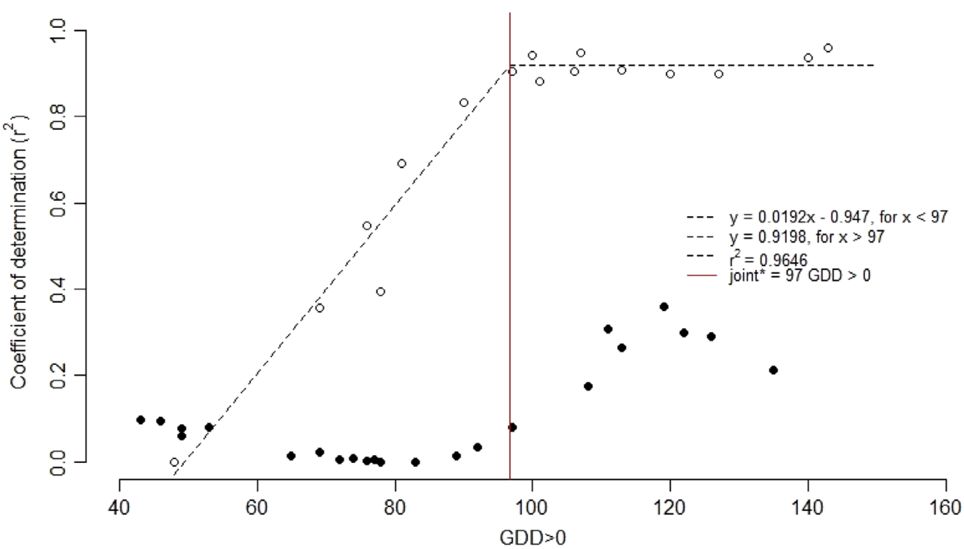

FIGURE 2 Correlation of normalized difference vegetation index versus winter wheat grain yield for readings collected over the season where the number of days from planting to sensing (growing degree days more than 0 [GDD > 0]) ranged from 48 to 143. Growing degree days was calculated as (Tmin + Tmax)/2 – 4.4°C. Data are for Experiment 502, Lahoma, OK, 2016 and 2017. Data not used for 2018 are represented by black dots

where NDVI and grain yield was highly correlated generally fell within the range of 90 and 120 d.

Plotting predicted yield over the entire season showed that at the beginning of the season (before reaching 90 GDD), the algorithm [Eq. (1)] overpredicts final grain yield. Furthermore, the reduced r^2 between actual and predicted yield before 100 GDD was encountered across all site-years in both trials (Figures 3a, 4a, 5a, 6a, 7a, and 8a). The prediction of YP_0 is the first and most critical step for calculating sensor-based, site-specific nutrient applications (Bushong, Mullock, Arnall, & Raun, 2018; Bushong et al., 2016; Tagarakis & Ketterings, 2017). The time at which sensor-based NDVI data are collected affects the accuracy of yield predictions and final N recommendations (Raun et al., 2005; Tagarakis and Ketterings, 2007).

The use of a harvest RI to estimate the response to applied N was first discussed by Johnson and Raun (2003). Mullen et al. (2003) disclosed that RI could be predicted by using

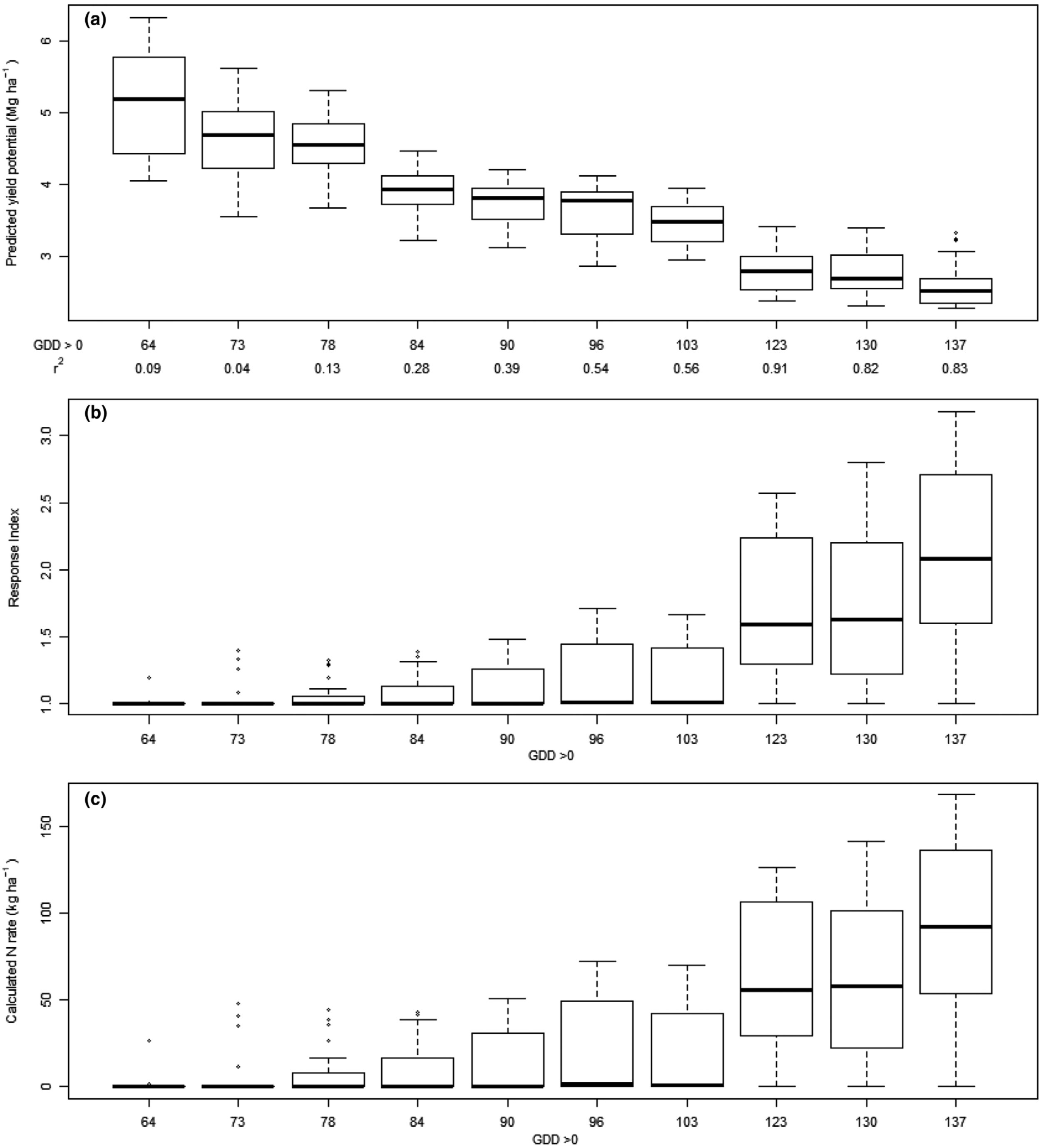

FIGURE 3 (a) Predicted yield potential (YP_0, Mg ha^{-1}) using sequential normalized difference vegetative index (NDVI) sensor readings coming from a range of pre-plant N treatments and the corresponding r^2 over the entire growing season. (b) Response index (NDVI in the non-N limiting plot divided by the NDVI of each treatment). (c) Recommended N application rate (kg ha^{-1}), indexed using the sum of growing degree days (growing degree days more than 0 [GDD > 0]), where days were summed when (Tmin + Tmax)/2 – 4.4°C > 0). Data are from Experiment 222, Stillwater, OK, 2016

mid-season, sensor-based NDVI measurements. The RI [Equation (2)], when plotted over the entire season, revealed that before 90 GDD there would not be any benefit to additional N (Figures 3b, 4b, 5b, 6b, 7b, and 8b). This means that NDVI values collected before 90 GDD would not be valuable or needed for recommending N. The practical significance of this is that less than optimal rates of N will be advised before 90 GDD, reducing the achievable final yield. This can further be seen from recommended N rates [Eq. (3)] over the different sites and years for both experiments (Figures 3c, 4c, 5c, 6c, 7c, and 8c). Additional N is recommended after 90 GDD, and the wider distribution of the boxplot indicates different

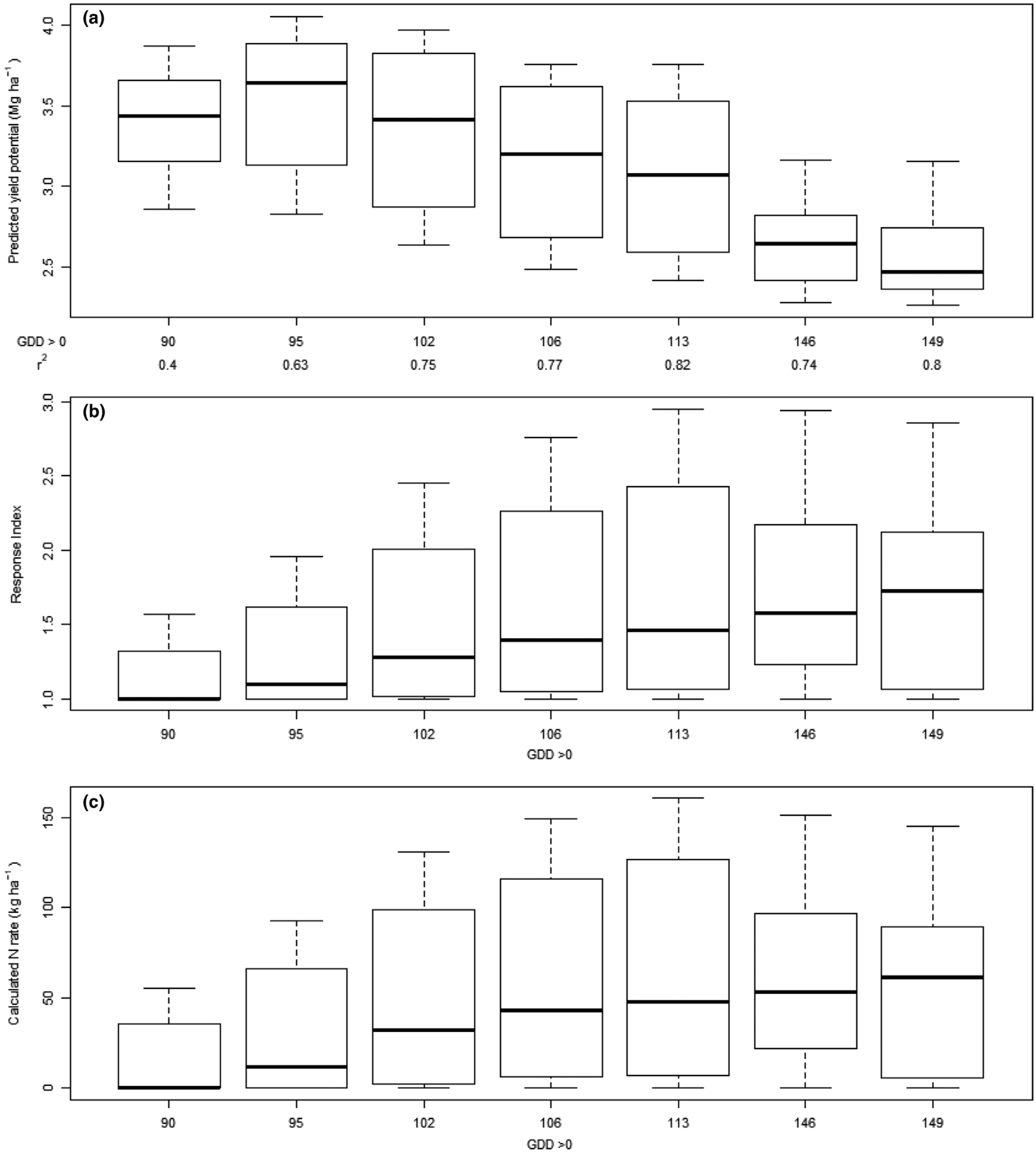

FIGURE 4 (a) Predicted yield potential (YP_0, Mg ha^{-1}) using sequential normalized difference vegetative index (NDVI) sensor readings coming from a range of preplant N treatments and the corresponding r^2 over the entire growing season. (b) Response index (NDVI in the non-N limiting plot divided by the NDVI of each treatment). (c) Recommended N application rate (kg ha^{-1}), indexed using the sum of growing degree days (growing degree days more than 0 [GDD > 0]), where days were summed when (Tmin + Tmax)/2 – 4.4°C > 0). Data are from Experiment 222, Stillwater, OK, 2017

N rate recommendations for different treatments. However, the spread of whiskers of these boxplots is to be expected because treatments received different preplant N rates (Tables 3 and 4), resulting in the recommendation of different N rates.

Relying on highly subjective morphological scales to determine the optimum time of day for sensing is and will continue to be cumbersome. Instead, having a metric that was a product of an existing and currently active environment will encompass a more refined within-season–specific method. This

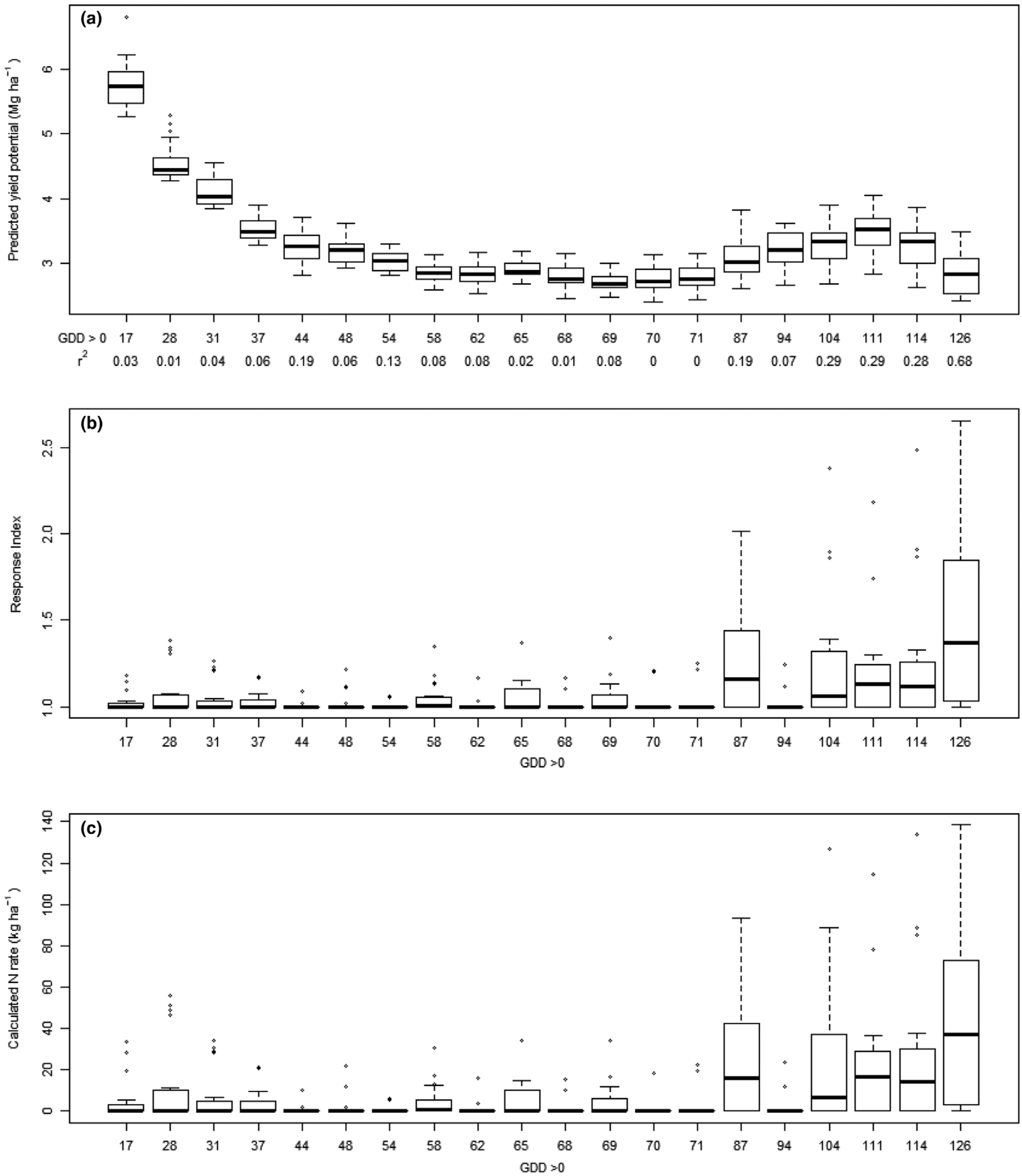

FIGURE 5 (a) Predicted yield potential (YP_0, Mg ha^{-1}) using sequential normalized difference vegetative index (NDVI) sensor readings coming from a range of preplant N treatments and the corresponding r^2 over the entire growing season. (b) Response index (NDVI in the non-N limiting plot divided by the NDVI of each treatment). (c) Recommended N application rate (kg ha^{-1}), indexed using the sum of growing degree days (growing degree days more than 0 [GDD > 0]), where days were summed when (Tmin + Tmax)/2 – 4.4°C > 0). Data are fom Experiment 222, Stillwater, OK, 2018

would in turn represent the exact environment that had been encountered for that specific year and, more importantly, for that particular site. This would also deliver an environment-specific N rate specifically tailored for each producer. Furthermore, such a methodology would remove the doubt and complexity of subjective morphological scales, which are known to vary by individual.

Had the boundary for using GDD > 0 as a numeric metric to define an optimum time for collecting sensor readings not been so clear, it would push this work back into a

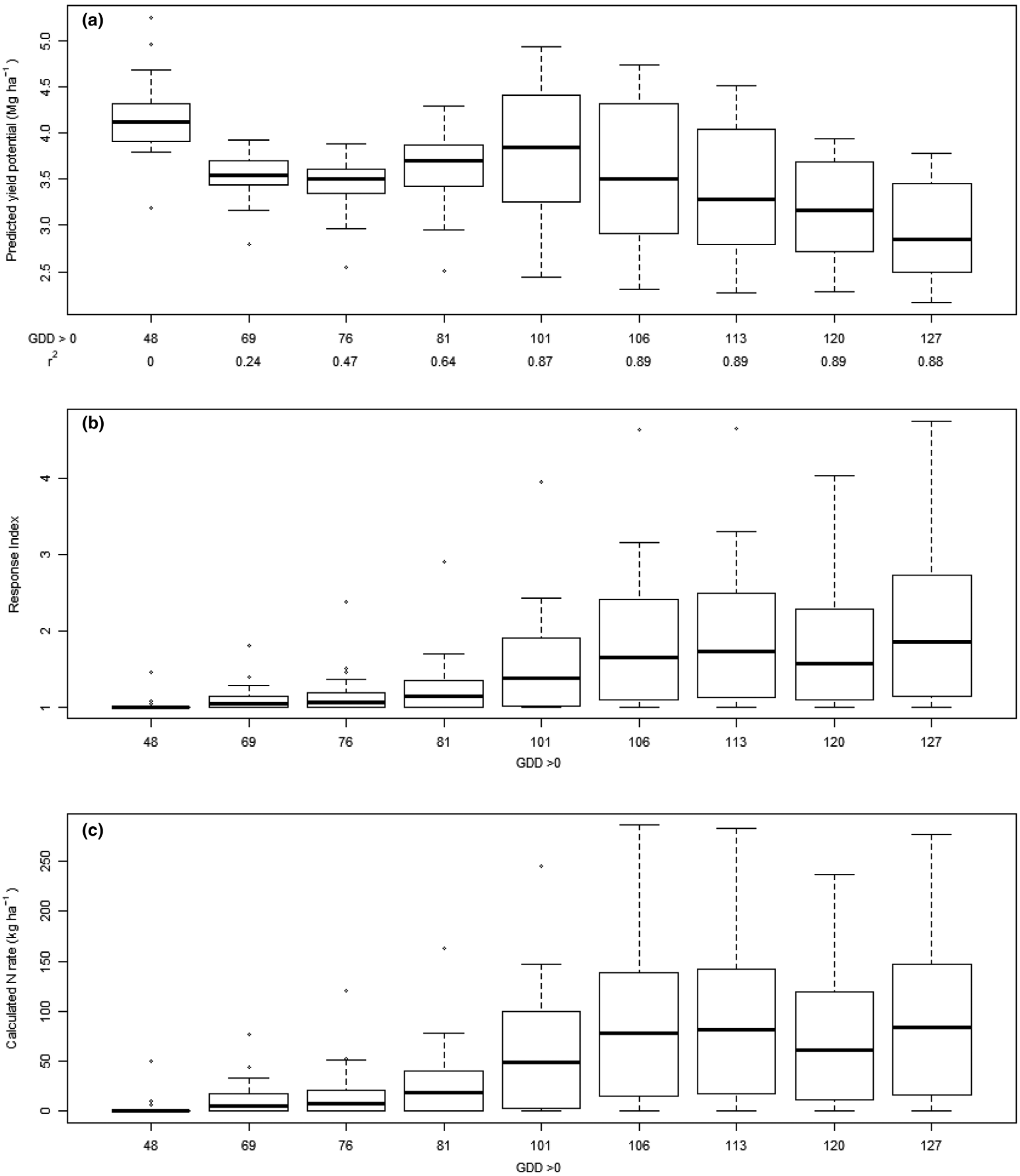

FIGURE 6 (a) Predicted yield potential (YP_0, Mg ha^{-1}) using sequential normalized difference vegetative index (NDVI) sensor readings coming from a range of preplant N treatments and the corresponding r^2 over the entire growing season. (b) Response index (NDVI in the non-N limiting plot divided by the NDVI of each treatment). (c) Recommended N application rate (kg ha^{-1}), indexed using the sum of growing degree days (growing degree days more than 0 [GDD > 0]), where days were summed when (Tmin + Tmax)/2 – 4.4°C > 0). Data are from Experiment 502, Lahoma, OK, 2016

morphological scale. However, the data over two different sites and three different years delivered highly consistent results in terms of defining how many days from planting to sensing where GDD > 0 were needed to reliably predict yield or yield potential.

Relying on a Feekes scale is not in itself a problem because this morphological scale has been incredibly useful. Instead, this work is a historical reminder that science, explicitly embedding climatological data within our yield prediction models, has delivered the clarity that was not previously present.

In general, it is not recommended that sites and/or years be combined due to the environmental differences that can change drastically and affect yield results (Raun et al., 2017).

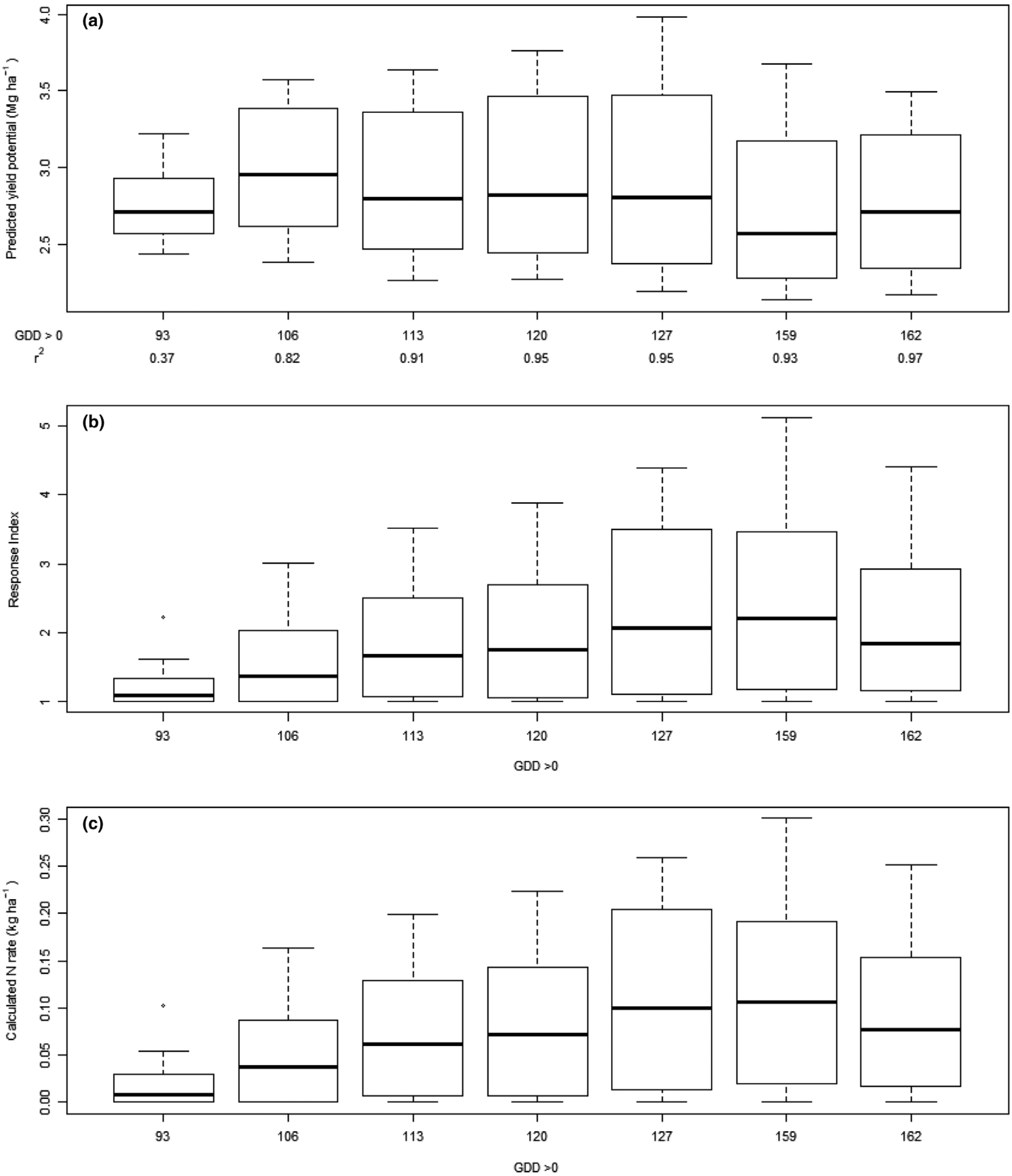

FIGURE 7 (a) Predicted yield potential (YP_0, Mg ha^{-1}) using sequential normalized difference vegetative index (NDVI) sensor readings coming from a range of preplant N treatments and the corresponding r^2 over the entire growing season. (b) Response index (NDVI in the non-N limiting plot divided by the NDVI of each treatment). (c) Recommended N application rate (kg ha^{-1}) indexed using the sum of growing degree days (growing degree days more than 0 [GDD > 0]), where days were summed when (Tmin + Tmax)/2 – 4.4°C > 0). Data are from Experiment 502, Lahoma, OK, 2017

In their previous work included 83 site years, coming from two long-term experiments, and showed that combining any two or three consecutive year periods was not advisable because the criterion for combining locations (e.g., homogeneity of error variance) over any two or three consecutive years had not been met (Raun et al., 2017). This present work represents the challenge of identifying a climatological boundary where yield or yield potential could be predicted

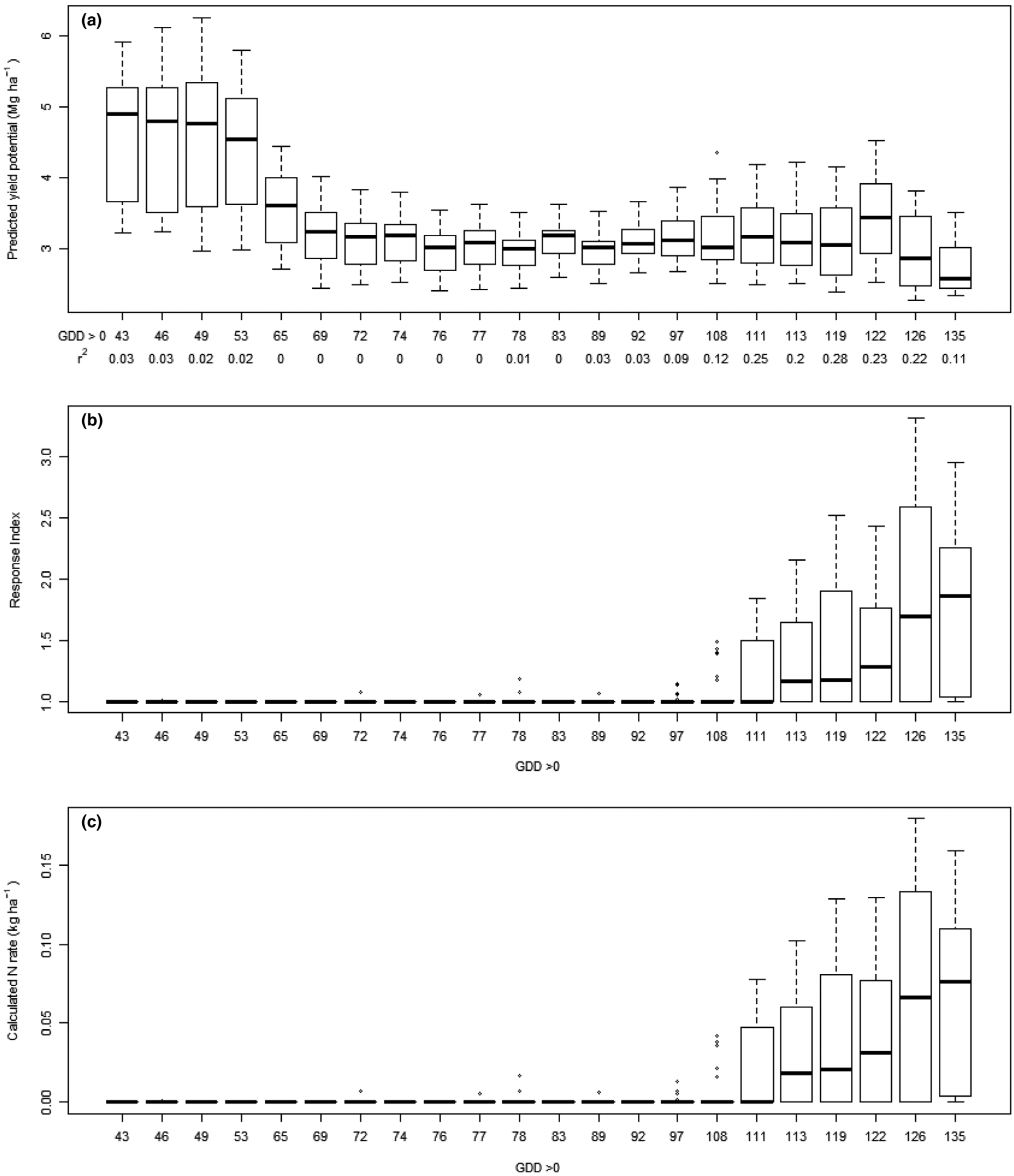

FIGURE 8 (a) Predicted yield potential (YP_0, Mg ha^{-1}) using sequential normalized difference vegetative index (NDVI) sensor readings coming from a range of preplant N treatments and the corresponding r^2 over the entire growing season. (b) Response index (NDVI in the non-N limiting plot divided by the NDVI of each treatment). (c) Recommended N application rate (kg ha^{-1}) indexed using the sum of growing degree days (growing degree days more than 0 [GDD > 0]), where days were summed when (Tmin + Tmax)/2 – 4.4°C > 0). Data are from Experiment 502, Lahoma, OK, 2018

and subsequently used to prescribe accurate mid-season fertilizer N rates based on using the yield potential parameter (Raun et al., 2005). For the 2018 cropping season and for both Experiment 222 and Experiment 502, no definite range in GDD > 0 could be established in terms of having improved correlation. There was a trend for very limited correlation up until 70 GDD > 0, which increased beyond that point (black circles in Figure 1 and 2). For an array of biological and agronomic reasons, including early-season moisture stress, plant biomass readings using NDVI were unreliable in 2018 at both locations.

4 | CONCLUSIONS

The year-to-year and site-to-site environmental variability that is present in agricultural fields leads to variable yield levels. This work identified definitive ranges within the growing season where NDVI sensor readings could be used to predict grain yield. Linear plateau models were used to determine the climatological period when the r^2 values (NDVI versus yield) peaked. Averaged over 3 yr and two sites, the optimum GDD > 0 needed to accurately predict yield potential was between 97 and 112. Using GDD > 0 as a numeric metric to delineate the best time and date to collect NDVI readings can then be used to prescribe mid-season fertilizer rates using established algorithms. Having numeric limits that surround in-season, GDD > 0 data are of value and may eliminate the use of highly subjective morphological scales. Critical GDD > 0 values from the Oklahoma Mesonet can then be accessed on a day-to-day, by-location basis for in-season producer use.

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